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# Advanced U-Net-Based Semantic Segmentation for Panoramic Dental X-Ray Analysis

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**Abstract** — *Medical image analysis in dental diagnostics encounters significant challenges, particularly in precisely segmenting anatomical components within panoramic X-ray images. This research investigates the use of U-Net-based deep learning architectures for semantic segmentation of dental structures. Six U-Net variations, including Vanilla U-Net, Dense U-Net and Attention U-Net, were examined to evaluate their segmentation performance. The dataset comprised panoramic dental X-ray images, which underwent pre-processing through Contrast Limited Adaptive Histogram Equalization (CLAHE) and resizing to ensure efficient training. Performance metrics such as Dice Coefficient, Intersection over Union (IoU), F1 Score and Accuracy were utilized for model evaluation. Results demonstrated that Vanilla U-Net with two convolutional layers achieved an effective balance between accuracy and computational cost. Future research aims to further enhance segmentation precision through architectural advancements and dataset enrichment.*

***Key Words:*** *Semantic Segmentation, U-Net, Panoramic Dental X-Ray, Deep Learning, Image Processing, Dice Coefficient, IoU, F1 Score.*

## 1. INTRODUCTION

Oral health plays a vital role in maintaining overall wellness, and the early detection of dental issues like cavities, gum diseases, and bone loss is essential for successful treatment. Panoramic dental X-ray imaging offers a detailed overview of oral structures, making it a valuable diagnostic resource. However, conventional analysis of these images primarily depends on manual evaluation by dentists and radiologists, which can be time-consuming and susceptible to human error. Additionally, factors like varying image quality, differences in patient anatomy, and overlapping features make precise diagnosis more challenging. In recent times, Artificial Intelligence (AI) and deep learning methods have demonstrated remarkable potential in automating medical image analysis and improving its accuracy [1], [2]. These AI-based systems have already shown success in cancer identification [3], lung disease prediction [4], and personalized treatments [5], highlighting their capability to transform healthcare.

In the case of medical imaging, semantic segmentation models have gained substantial attention among deep learning approaches. U-Net stands out as a widely adopted architecture which is focused and designed for biomedical image segmentation tasks. It features two major things a encoder and decoder framework combined with skip connections, enabling accurate pixel-level classification while retaining spatial information [6]. Over time, various enhanced versions of U-Net, including Dense, Attention, Residual, and Nested, have been introduced to boost segmentation accuracy, improve feature transmission, and increase computational effectiveness [7]. Additionally, lightweight deep learning models have been explored to enhance efficiency while maintaining high accuracy in panoramic dental X-ray segmentation [8]. AI-based models have also been utilized in various medical imaging fields, including transformer-based DL networks for dental segmentation [9] and CNN-based automated analysis of dental implants in CBCT images [10].

This study focuses on evaluating and comparing six U-Net variants for segmenting panoramic dental X-ray images to identify the most effective model for clinical applications. The dataset undergoes pre-processing, annotation, model training, and validation, with segmentation performance evaluated using Dice Coefficient, Intersection over Union (IoU), F1 Score and Accuracy. Previous research has demonstrated the effectiveness of multi-scale feedback feature refinement U-Net for medical image segmentation [11] and the application of attention mechanisms in U-Net for enhanced segmentation [12]. Additionally, advancements in computer-aided diagnostic (CAD) systems have facilitated the integration of AI-driven segmentation with real-time clinical decision-making tools [13]. By identifying the optimal U-Net variant for dental X-ray segmentation, this research aims to advance automated dental diagnostics and contribute to the growing field of AI-powered healthcare solutions.

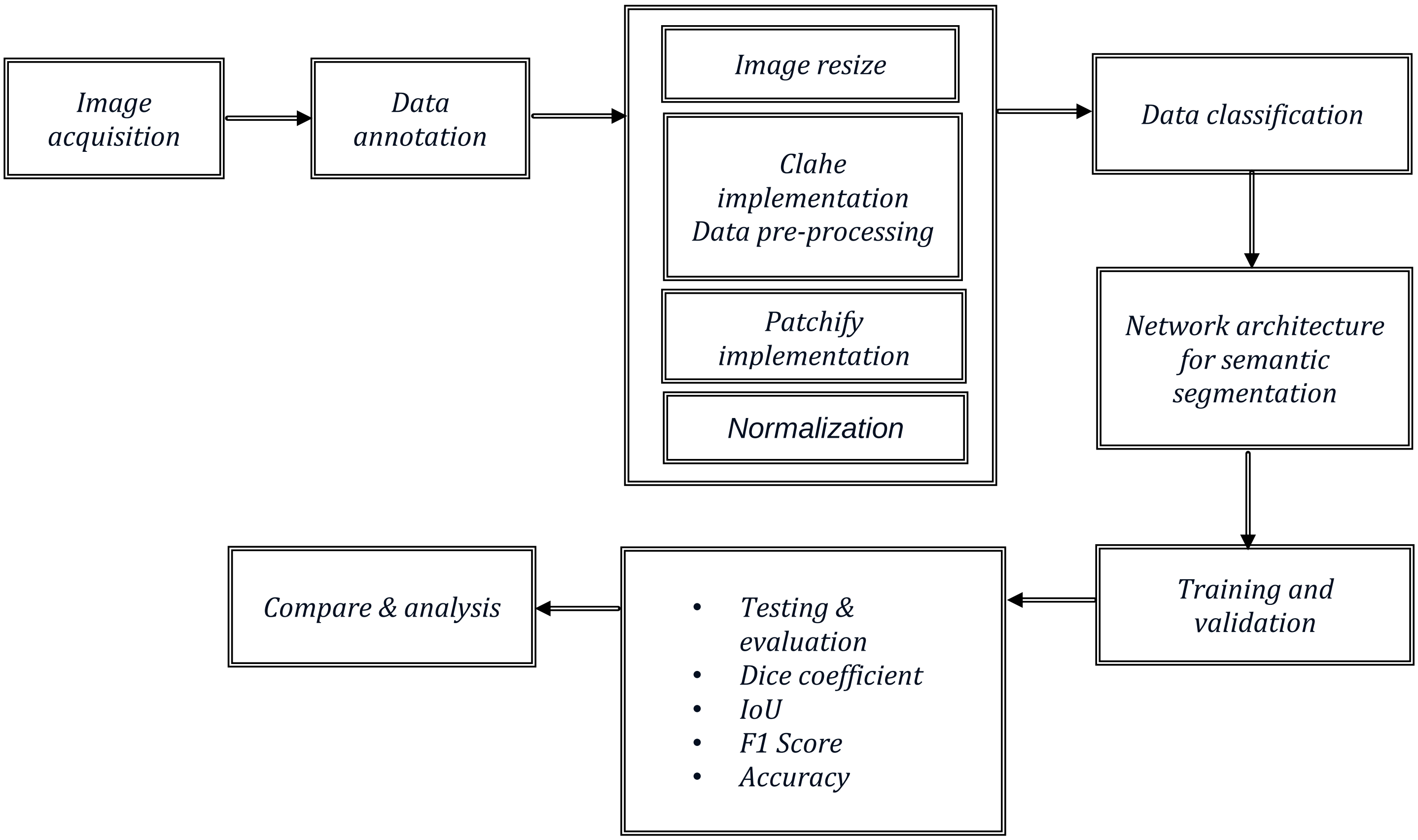


**Fig-1** Block Diagram of Dental X-Ray Image Segmentation Process

## 2. METHODOLOGIES

The methodology adopted for segmenting dental X-ray images is based on a systematic pipeline. Initially, panoramic dental X-ray images are acquired. These images are then annotated by assigning ground truth labels for model training. The pre-processing phase involves several enhancement techniques, including image resizing, applying CLAHE, patchify transformation, and normalization to improve image clarity. Subsequently, the processed data is utilized to train various U-Net-based deep learning models for semantic segmentation. The models are evaluated through performance metrics such as Dice Coefficient, IoU, F1 Score, and Accuracy, enabling comparative analysis to identify the optimal model for dental diagnostics.

### 2.1. DATA COLLECTION

The input dataset comprises panoramic X-ray (OPG) images collected from an open-source Kaggle dataset. Additionally, raw images were captured using a Xiaomi Redmi Note 9 Pro 64 MP camera to expand the dataset. The images represent patients of various age groups and genders, with a focus on middle-aged individuals. Some images exhibit blue and grey tints, highlighting variations in imaging conditions. The dataset ensures diversity by including images of children, men and women, capturing a range of dental structures. The collected images serve as input for the segmentation models, providing real-world variability essential for robust model performance.


**Fig-2 Input image**

**2.2. DATA ANNOTATION**

Label Studio was employed to generate annotated training data by marking the dental regions in the X-ray images. The "Semantic Segmentation Using Mask" feature was used for labeling, where a fixed color code (R=255, G=76 and B=66) was applied to distinguish tooth regions consistently. For each image, a region of interest called "Tooth" was defined, and manual masking was performed accordingly. These labeled masks serve as the ground truth for training the U-Net segmentation model. The annotated dataset enables the deep learning model to accurately identify tooth boundaries, ultimately enhancing segmentation results.


**Fig-3 Data Annotation Process for Panoramic Dental X-Ray Images**

**2.3. DATA REFINEMENT PROCESS**

To enhance image quality and standardize input data for the model, multiple pre-processing steps were applied. Image resizing was performed where the original 4000 × 3000-pixel X-ray images were cropped to remove irrelevant areas and resized to 1024 × 1024 pixels to ensure compatibility with U-Net models. CLAHE was employed with a clip limit of 2.0 and a tile grid size of (8,8) to enhance local contrast and amplify fine details in regions with low visibility. This technique effectively mitigates the effects of uneven illumination and improves the visibility of anatomical structures within the dental X-ray images, facilitating better segmentation performance during model training. Since U-Net performs better with small image patches, the 1024 × 1024 images were divided into 256 × 256 patches using a 4 × 4 grid through Patchify implementation, which enhances model efficiency and allows finer segmentation. Pixel intensity values were normalized using linear scaling, converting values from the range 0-255 to 0-1 to standardize input across the dataset. This ensures that all input images have uniform pixel intensity distributions, improving learning stability.

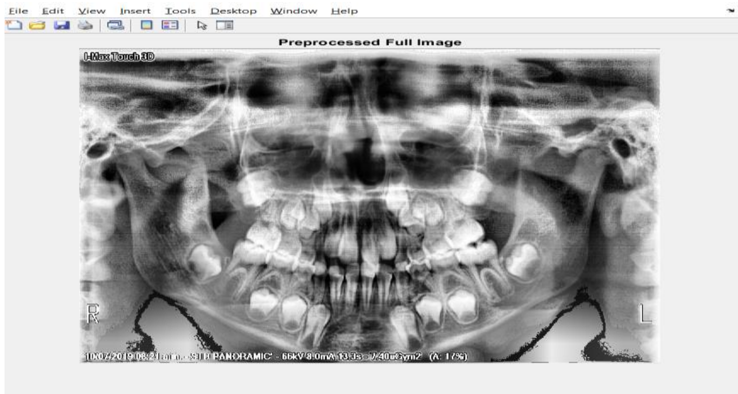


**Fig-4 Preprocessed Full Image**

### 2.4. DATA CLASSIFICATION AND SPLITTING

The dataset was divided into training, validation, and testing sets in the ratio of 8:1:1, using a fixed random state value of 42 to maintain reproducibility. Upon completion of the image enhancement procedures, a total of 6224 image-mask patches were created. Out of these, 4978 patches were assigned for training, 623 patches for case of validation, and 623 patches for testing. This systematic data division will ensure better generalization of model and reduces the possibility of overfitting to specific data characteristics.

### 2.5. NETWORK ARCHITECTURE FOR SEMANTIC SEGMENTATION

A U-Net based deep learning framework was employed to perform semantic segmentation on dental panoramic X-ray images. U-Net, a fully convolutional neural network (FCN) with an encoder-decoder architecture, facilitates precise pixel-wise classification. The network effectively captures spatial and contextual information while preserving image resolution through its skip connections. To enhance the morphological separation of adjacent structures within the images, a pixel-wise weight map w(x) was utilized, mathematically defined as:

$$w(x) = w_c(x) + w_0 . \exp\left(-\frac{\left(d_1(x) + d_2(x)\right)^2}{2\sigma^2}\right)$$

here w_c(x) represents the base weight map, $d_1(x)$ and $d_2(x)$ are distances to the nearest and second-nearest boundaries, and $w_0 = 10$ and $\sigma \approx 5$ pixels in this implementation. Multiple U-Net variants were explored, including Dense U-Net, Vanilla U-Net, Attention U-Net and Residual U-Net. These divisions enhance performance by improving feature extraction, localization and segmentation accuracy.


**Fig-5 Segmented Output of Dental X-Ray Using U-Net Model**

### 2.6. TRAINING AND EVALUATION METRICS

The training phase utilized the Adam optimizer with a learning rate of 0.0001 to optimize the U-Net model parameters. A batch size of 16 was employed, and the model was trained over 100 epochs using 4978 image-mask pairs for training, while 623 pairs were reserved for validation.

To understand the segmentation performance of the model, several evaluation metrics were employed. The Dice Coefficient, in particular, was used to quantify the similarity between the predicted segmentation masks and the ground truth annotations. It is mathematically expressed as:

$$Dice = \frac{2\,|X \cap Y|}{|X| + |Y|}$$

where X denotes the predicted and y denotes ground truth segmentation masks. Intersection over Union (IoU) evaluates segmentation quality by measuring the overlap ratio and is given by:

$$\text{IoU} = |X \cap Y| \,/\, |X \cup Y|$$

The F1 Score balances precision and recall for accurate segmentation results and is computed using:

$$F1 = \frac{2 \times (\text{P} \times \text{R})}{(\text{P} + \text{R})} \ (where\ P = Precision\ and\ R = Recall)$$

Accuracy represents the ratio of correctly predicted pixels to the total number of pixels in the dataset and is defined as

$$\text{Accuracy} = (\text{TP} + \text{TN}) \,/\, (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

These metrics collectively assess the efficacy of U-Net-based models in segmented dental structures, ensuring optimal performance for clinical applications.

## 3. RESULT AND DISCUSSION

The U-Net-based model demonstrated exceptional performance in segmenting dental X-ray images, achieving a Dice Coefficient of 0.9904, IoU of 0.9809, F1 Score of 0.9904, and Accuracy of 0.9915. These impressive metrics highlight the model's ability to accurately identify dental structures with minimal segmentation errors. Enhancing image contrast using techniques like CLAHE improved the clarity of low-contrast regions, leading to more accurate segmentation. Additionally, the use of patch-based segmentation allowed the model to focus on smaller regions, enhancing its ability to extract relevant features. However, slight challenges were encountered in cases with overlapping structures or varying contrast, occasionally causing misclassifications. Comparisons with other methods revealed that U-Net variants such as Dense and Residual performed better when dealing with complex dental structures.

The study further compared six different architectures of it, including two-layer and three-layer versions, on tooth segmentation in panoramic dental X-rays. All models delivered strong performance, with only slight variations in Dice Coefficient scores, suggesting minimal differences in segmentation quality. These results offer valuable insights for selecting the most suitable model for dental diagnostic purposes. Nonetheless, issues like computational load and inference speed need further optimization. Future improvements could include the integration of transformer-based models, attention mechanisms, and post-processing techniques to enhance accuracy and robustness across varied datasets. The study underscores the potential of DL approaches in supporting AI-assisted dental diagnostics.

## 4. CONCLUSION

This study investigated the use of U-Net-based deep learning models for segmenting dental structures in panoramic X-ray images. The experimental results confirmed the high precision and reliability of semantic segmentation techniques in dental image analysis. Pre-processing strategies such as CLAHE, normalization, and patch-based segmentation played a crucial role in enhancing the model's ability to detect fine structural details, resulting in improved segmentation performance. Although the model achieved impressive metrics—including a Dice Coefficient of 0.9904 and an IoU of 0.9809—minor challenges persisted in cases with overlapping structures and inconsistent contrast. The findings provide valuable direction for selecting optimal models to ensure accurate and efficient dental segmentation.

Looking ahead, future work will aim to optimize model performance by improving processing speed without compromising accuracy. Enhancing computational efficiency, incorporating hybrid architectures, and refining post-processing steps will be key areas of focus. These advancements hold promise for boosting segmentation precision across varied datasets. Overall, the results underscore the transformative role of AI-powered image analysis in dentistry, supporting the development of automated tools that can assist dental professionals in making more informed clinical decisions.

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